Growth Prospects and the Trade Balance in Advanced Economies

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Abstract

Does an improvement in growth prospects lead to a fall in the trade balance? The answer in the literature with a strong focus on the U.S. economy is yes. However, we do not find that improved growth prospects (news shocks) necessarily lead to negative trade balance effects in the G7 countries. We develop a novel news shocks identification scheme, apply it to country-level vector autoregressions (VARs), and obtain the following results. While in the U.S. and Germany, news shocks induce a deterioration of the trade balance, in other G7 countries, news shocks have positive trade balance effects. The differences in the trade balance effects across the G7 countries are mainly due to heterogeneous reactions of exchange rates, labor markets, wealth effects, and monetary policy. Therefore, policy recommendations aimed at reducing the trade imbalances through productivity-enhancing reforms in advanced economies might not entail the targeted effects.

JEL-Code: F41, E32, F32, D83, O40

Keywords: Terms of trade; trade balance; news shocks; productivity; learning

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1 Introduction

Does an improvement in growth prospects lead to a fall in the current account balance? This question is highly relevant as the persistence of global current account imbalances in the last decades has prompted a lot of research and triggered major policy debates. Prominent examples are the high current account surpluses of China and Germany and the subsequent policy reactions from the present U.S. government. To fix these imbalances, economic officials often call for productivity-enhancing reforms leading to an improvement in growth prospects in advanced economies whose economic performance is lagging behind the U.S.\textsuperscript{1} The main idea behind this policy recommendation is that improved growth prospects create a positive wealth effect for households, which stimulates consumption expenditures. The increase in households’ demand together with anticipated productivity gains raise firms’ investment. Overall, higher domestic absorption increases imports, which leads to a decline in net exports.\textsuperscript{2}

Our study challenges this policy recommendation and asks whether an improvement in growth prospects indeed generates a deterioration of the trade balance in the G7 countries. We focus on the trade balance, rather than the current account, because we want to abstract from the fluctuations in primary income caused by other factors that are not related to our shock of interest. Furthermore, since an improvement in a country’s growth prospects cannot be observed directly, we capture the latter by relying on the concept of technological news shocks. The literature on news shocks builds around the idea that forward-looking agents observe productivity-enhancing changes in technology well in advance of their effect on the economy’s productive capacity (Beaudry and Portier, 2004). These shocks diffuse slowly over time and result in predictable and persistent changes in the productivity level.

There is a large literature that relates news shocks to changes in agents’ expectations about the long-run economic developments. To do so, much of the applied news literature relies on proxy measures, such as stock prices (Beaudry and Portier, 2006), consumer confidence (Barsky and Sims, 2012), forecast data (Miyamoto and Nguyen, 2014), survey expectations of long-run (6 to 10 years ahead) output growth (Hoffmann, Krause, and Laubach, 2019), forecast revisions from professional forecasters (Cascaldi-Garcia, 2019), changes in the expected share of U.S. income (Engel and Rogers, 2006), and consumption and income data (Aguiar and Gopinath, 2007). Kurmann and Otrok (2013) show that movements in the slope of the term structure of interest rates are mainly due to news about future productivity. Furthermore, Cascaldi-Garcia and Vukotić (2019) use firm-level data on patent grants and subsequent reactions of their stocks to extract the news shocks. Finally, Arezki, Ramey, and Sheng (2017) use the worldwide giant oil and gas discoveries as a directly observable measure of news shocks about future output.

\textsuperscript{1}See, for example, European Commission (2019) and International Monetary Fund (2019).

\textsuperscript{2}Another transmission mechanism highlighted in the literature is through international capital flows. An improvement in domestic growth prospects relative to other countries is likely to be associated with future increasing returns on investment. As a result, the domestic economy becomes a profitable investment destination and thus attracts more capital. The latter induces a fall in net exports (net capital exports).
The empirical literature regarding the effects of exogenous technological improvements on the trade balance focuses strongly on the U.S. economy (see, for example, Corsetti, Dedola, and Leduc, 2008, 2014; Enders and Müller, 2009; Enders, Müller, and Scholl, 2011). Moreover, this literature studies the effects of the unanticipated changes in technology, while we are interested in the relationship between the anticipated technology shocks (news shocks) and the trade balance. Nonetheless, the empirical results from the bulk of the reviewed literature demonstrate that a positive technology shock in the U.S. economy triggers a deterioration of the trade balance. This result is complemented by the work of Aguiar and Gopinath (2007) and Hoffmann et al. (2019), who show that a fall in the trade balance is the optimal response of households and firms to changing growth prospects.3

In our study, the focus on the effects of news shocks rather than the unanticipated technology shocks is motivated by the following considerations. First, we are primarily interested in analyzing the trade balance fluctuations resulting from an improvement in domestic growth prospects, for which anticipated technological innovations play a crucial role. Second, it can be shown that unanticipated and anticipated technology shocks might have different implications for fluctuations in the trade balance. For example, Nam and Wang (2015) provide evidence for the U.S. economy indicating that unanticipated and anticipated technology shocks induce distinct dynamics for the trade balance and international prices. Thus, the large literature dealing with the trade balance effects of unanticipated technology shocks could be misleading for our research question.

From a theoretical point of view, the intertemporal approach to the trade balance (Obstfeld and Rogoff, 1996) suggests that unanticipated and anticipated changes in technology imply different incentives for savings and investment decisions (Barsky, Basu, and Lee, 2015). The unanticipated technology shock increases current and expected future income. However, consumption does not increase by the same amount as output in the current period. As a result, the trade balance improves. By contrast, the anticipated changes in future economic developments, which we capture by extracting the news shocks, induce a higher consumption in the current period even though the current output is still produced with the old technology. It follows that the savings behavior plays an important role for the negative trade balance response following an anticipated technology shock.

The effects of the anticipated improvements in future output growth on investment and hours worked are ambiguous. Following Jaimovich and Rebelo (2009), Schmitt-Grohé and Uribe (2012), and Fratzscher and Straub (2013), these effects crucially depend on the specification of the preferences that govern the wealth elasticity of labor supply and other model assumptions, like investment adjustment costs, variable capacity utilization, the substitution elasticity between domestic and foreign goods, home bias concerning domestic goods, and labor and financial market rigidities. Thus, it is not obvious that a favorable news shock always leads to an expansion in domestic absorption and consequently to a decline in the trade balance.

3Engel and Rogers (2006) develop an intertemporal model and show that the high U.S. current account deficit in 2006 is consistent with an expected increase in the U.S. share in world output.
Therefore, the aim of this paper is to enhance the understanding of the trade balance effects resulting from an improvement in growth prospects by providing empirical evidence for the major advanced economies.

The main news shocks identification approaches in the VAR literature are proposed by Barsky and Sims (2011) and Kurmann and Sims (2019). Both studies apply their identification procedures using a utilization-adjusted total factor productivity measure determined by Fernald (2014) (henceforth referred to as PTFP) for the U.S. economy. Since such series are not available for other countries, we instead rely on labor productivity as target technology measure in our baseline calculations. Importantly, labor productivity is not corrected for cyclical variations in factor utilization. Therefore, to isolate the anticipated technology shocks from the demand and unanticipated technology shocks, we develop a novel news shocks identification scheme. Specifically, we first identify the unanticipated and anticipated technology shocks and separate them from other structural shocks using the medium-run identification technique proposed by Uhlig (2004a,b). In a second step, we disentangle the two technology shocks using the feature that the unanticipated technology shocks explain a larger share of the forecast error variance (FEV) of labor productivity in the short run compared to news shocks.

Our identified news shocks lead to a gradual and persistent increase in the productivity level, which is accompanied by a transitory increase in productivity trend growth. The results for the U.S. are in line with the literature and show that an improvement in growth prospects leads to a persistent deterioration of the trade balance. We find that this decline in the trade balance is mainly due to an expansion of imports, which is driven by a rise in domestic absorption. Both consumption and investment display a positive hump-shaped response to a news shock. We explain these findings mainly by a strong wealth effect and an expansionary monetary policy reaction causing a decline in the real interest rate. The U.S. terms of trade appreciate and act as an amplifier of the wealth effect.

In contrast to the U.S., we find that on average across the G7 countries, news shocks do not have a negative effect on the trade balance. If any, this effect is positive. We discuss several transmission channels leading to this finding. For example, for Japan, we stress the important role of the terms of trade in explaining the trade balance dynamics. Even a strong increase in the Japanese domestic absorption after a favorable news shock does not lead to a deterioration of the trade balance. For France, we find that a positive news shock causes a decline in imports via a contraction in domestic absorption—both consumption and investment fall. We find for the French economy that the real interest rate rises and, therefore, causes a curbing effect on domestic absorption. Moreover, hours worked decline by a large amount with negative repercussions on consumption and investment.

Overall, we conclude that productivity-enhancing changes in technology that lead to an improvement in growth prospects do not necessary generate a fall in the trade balance or, in a broader view, the current account balance. This result is particularly relevant in light
of economic policy recommendations raised by international organizations that emphasize the negative link between the fluctuations in the trade balance and growth prospects.\textsuperscript{4}

The remainder of this paper proceeds as follows. In Section 2, we discuss the transmission of news shocks to the trade balance based on the intertemporal approach. In Section 3, we review the recent literature on news shocks and propose an alternative identification approach. In Section 4, we discuss our key results. In Section 5, we check the robustness of our baseline results. Section 6 concludes the analysis.

2 The effects of expectations on the trade balance

Engel and Rogers (2006) and Hoffmann et al. (2019) show that the U.S. current account deficit is consistent with the intertemporal optimizing behavior of forward-looking agents to expected changes in future economic developments. Aguiar and Gopinath (2007) reach similar conclusions studying the current account fluctuations in emerging markets. Following Beaudry and Portier (2006, 2014), changes in agents’ expectations about future economic developments occur due to the arrival of news that is useful for predicting future economic fluctuations. The authors stress that while there are many sources of changes in expectations concerning different macroeconomic variables, the literature focuses on the role of technological news, that is expected future changes in productivity level.\textsuperscript{5}

When analyzing the forces behind trade balance fluctuations, it is crucial to distinguish between two structural shocks that affect the aggregate productivity level (see, for example, Barsky and Sims, 2011). First, the unanticipated technology shock that induces an immediate increase in the productivity level. Second, the anticipated technology shock—the news shock—that diffuses slowly over time and therefore generates a gradual and persistent increase in the productivity level. Following the expositions in Barsky and Sims (2011), the stochastic process characterizing the aggregate level of productivity, denoted by $\ln A_t$, can be represented by the following moving average process:

$$
\ln A_t = \begin{bmatrix} B_{11}(L) & B_{12}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix},
$$

where $\varepsilon_{1t}$ is the unanticipated technology shock and $\varepsilon_{2t}$ is the news shock. The timing assumptions related to the effects of $\varepsilon_{1t}$ and $\varepsilon_{2t}$ on $\ln A_t$ are crucial to isolate the two shocks. While $\varepsilon_{1t}$ is allowed to affect $\ln A_t$ contemporaneously, the literature identifies the news shock

\textsuperscript{4}The negative link between the trade balance and growth prospects provides the basis for several policy statements proposed by the European Commission to the German government regarding its current account surplus.\textsuperscript{5}Schmitt-Grohé and Uribe (2012) provide insights into how news about future changes in different macroeconomic variables affects the behavior of forward-looking agents. Hoffmann et al. (2019) study the effects of shocks to productivity under different assumptions about the agents’ expectations formation process. They show that under the assumption of imperfect information about changes in technology, news shocks are able to explain the gradual and persistent decline of the U.S. current account.
Thus, forward-looking agents incorporate the *news* about the future productivity level into their behavior before the expected changes materialize.

The unanticipated technology shock and the news shock imply different incentives for agents’ savings and investment decisions (see, for example, Barsky et al., 2015). Specifically, Aguiar and Gopinath (2007), Hoffmann et al. (2019), and Nam and Wang (2015) show that the two types of shocks to productivity have markedly different implications for the trade balance. The standard intertemporal approach to the current account (Obstfeld and Rogoff, 1996) suggests that while the unanticipated technology shock generates a positive trade balance effect, the news shock leads to a deterioration of the trade balance. The difference in these effects is mainly driven by the agents’ savings behavior. Although the news shocks induce a delayed improvement in the productivity level, agents are willing to increase their current spending in the expectation of a persistently higher future income. As a result, a news shock is associated with a positive wealth effect, causing a stronger reaction of the current consumption compared to output. Overall, savings decline and the trade balance deteriorates. By contrast, in case of an unanticipated technology shock, consumption responds less than output, leading to an increase in savings and an improvement in the trade balance.

The effects of news shocks on investment and labor supply are ambiguous. Jaimovich and Rebelo (2009), Schmitt-Grohé and Uribe (2012), and Fratzscher and Straub (2013), for example, show that the reactions of these variables to news shocks crucially depend on the specification of the preferences that govern the wealth elasticity of labor supply and other model assumptions, like investment adjustment costs, variable capacity utilization, the substitution elasticity between domestic and foreign goods, home bias concerning domestic goods, and labor and financial market rigidities. A similar statement can be made for the unanticipated technology shocks. Overall, it is often the case that in the same theoretical model, the news shock and the unanticipated technology shock lead to different reactions of investment and labor. It is, therefore, important to distinguish between both shocks in our analysis.

Our research focuses on the consequences of technological news as we are primarily interested in the effects of improved growth prospects on the trade balance. While the empirical literature on the trade balance effects of unanticipated technology shocks is quite vast (see, for example, Corsetti et al., 2014; Enders and Müller, 2009), the research concerning the link between news shocks and the trade balance is scarce.

We are aware of four notable exceptions. Nam and Wang (2015) analyze the effects of news shocks for the U.S. economy and find a significant deterioration of the trade balance accompa-

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6 Barsky and Sims (2011) assume that news shocks have no contemporaneous effect on \( \ln A_t \), which translates into imposing the impact zero restriction \( B_{12}(0) = 0 \) in (1).

7 In the presence of relative price movements in response to these shocks, the explanation of the trade balance effects of the two types of shocks to productivity is even more challenging. In particular, Nam and Wang (2015) demonstrate that the terms of trade are an important transmission channel for trade adjustments and cross-country wealth effects. Enders and Müller (2009) provide a detailed analysis of the transmission of unanticipated technology shocks to the U.S. trade balance in the presence of the terms of trade adjustments to these shocks.
nied by a sizable appreciation of the terms of trade in response to these shocks. Fratzscher and Straub (2013) identify news shocks in a structural VAR (SVAR) with sign restrictions derived from a two-economy model. In a sample of 38 industrialized and emerging market economies, they find highly heterogeneous trade balance effects of news shocks. However, on average, Fratzscher and Straub (2013) find a deterioration of the trade balance in response to these shocks. Similarly, Kamber, Theodoridis, and Thoenissen (2017) find a negative response of the trade balance and an appreciation of the terms of trade following a news shock for Australia, Canada, New Zealand and the U.K.

Finally, Arezki et al. (2017) depart from the mainstream news shocks literature and use the worldwide giant oil and gas discoveries as a directly observable measure of news shocks to study their effects on the current account. In their special case of natural resource discoveries, their news shocks are characterized by a quite large economic importance, very high capital intensity, and a long delay between the arrival of news and its realization. Arezki et al. (2017) find a deterioration of the current account in the first years after an oil or gas discovery.

We provide new evidence on the link between technological news shocks and the trade balance by introducing a novel identification procedure. Specifically, we aim at identifying structural shocks that induce a delayed and permanent improvement in the productivity level, but do not affect it immediately. In the transition period to the permanently higher productivity level, this shock is expected to induce higher growth rates of productivity, which we associate with an improvement in growth prospects. The increase in the productivity growth rates is, however, only transitory. Our empirical analysis and, in particular, our identification approach, face several challenges:

1) We need to isolate unanticipated and anticipated technology shocks from other structural shocks (e.g. demand shocks). The other structural shocks are not allowed to affect the true productivity level of the economy.

2) Our identification approach needs to separate unanticipated and anticipated (news) technology shocks.

3) We need to ensure that the news shocks affect the future productivity level permanently. Put differently, our news shock has only a transitory effect on productivity trend growth.

3 Identification of news shocks

3.1 Revisiting the basic identification approaches

Our identification of news shocks draws on two SVAR approaches proposed in the literature. The first approach, introduced by Barsky and Sims (2011) (BS), extracts the news shocks using the medium-run identification procedure developed by Uhlig (2004a,b). BS identify the news as the shock that is orthogonal to the contemporaneous innovation in the cyclically

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8A comprehensive summary of the literature on news shocks can be found in Beaudry and Portier (2014).
adjusted technology measure and that best explains future variations in technology. Unlike Uhlig (2004a,b), who uses labor productivity as targeted technology measure in the VAR, BS use PTFP by Fernald (2014).

The second approach is proposed by Kurmann and Sims (2019) (KS). KS show that the results in BS are sensitive to revisions in PTFP and therefore develop a robust identification of news shocks that differs from the BS model in two aspects. First, instead of cumulatively maximizing the FEV shares over all horizons from impact onward, KS extract the news shocks that account for the maximum FEV share of PTFP at one long horizon using the Max Share approach by Francis, Owyang, Roush, and DiCecio (2014). This approach should substantially reduce the contribution of the non-technological component that may remain in PTFP to the extracted news shock. Second, KS drop the zero restriction because it may lead to biased estimates of the impact responses to the news shock. If PTFP is an inaccurate measure of true technology, then its non-technological component reacts immediately to a news shock and thus violates the orthogonality assumption. Further, forward-looking agents may update their expectations about future productivity based on currently realized changes in technology (Barsky et al., 2015).

The medium-run identification technique

Consider the reduced-form moving average (MA) representation of $Y_t$, a $k \times 1$ vector of endogenous variables at time $t$, with productivity measure ordered first:

$$Y_t = C(L)u_t,$$

where $u_t$ is a vector of prediction errors with covariance matrix $\Sigma_u$. The vector of structural shocks $\varepsilon_t$ can be represented as a linear combination of prediction errors $u_t = A\varepsilon_t$. To obtain $\varepsilon_t$, the impact matrix $A$ must satisfy $\Sigma_u = AA'$, which given the symmetry of $\Sigma_u$ is not unique. The Cholesky decomposition of $\Sigma_u$ gives such a matrix $\hat{A}$, which allows to summarize the entire space of acceptable impact matrices as $A = \hat{A}Q$, where $Q$ is a $k \times k$ orthonormal matrix ($QQ' = I$). Thus, the structural MA representation of $Y_t$ takes the form:

$$Y_t = C(L)\hat{A}Q\varepsilon_t.$$ (3)

The idea of the medium-run identification approach by Uhlig (2004b) is to find the structural shock that accounts for the largest FEV share of some target variable $y_{i,t}$ in $Y_t$ over the forecast horizons $h = h \leq \bar{h}$. The $h$-step ahead forecast error of $y_{i,t}$ can be written as:

$$y_{i,t+h} - E_t y_{i,t+h} = e_t \left[ \sum_{l=0}^{h-1} C_l \hat{A}Q\varepsilon_{t+h-l} \right],$$ (4)

9In contrast to BS and KS but similar to Uhlig (2004a,b), Francis et al. (2014) use a VAR with labor productivity to identify the unanticipated technology shocks.

10The constant is omitted to save on notation. The estimation of an unrestricted VAR gives $C(L)$ and $\Sigma_u$.

11$h$ and $\bar{h}$ are, respectively, the starting and ending points of the maximization horizon.
where $e_i$ is a column vector with one in the $i$-th position and zeros elsewhere. The shock explaining most of the FEV of the $i$-th variable in $Y_t$ results from the maximization problem:

$$q_1^* = \arg \max_{q_1} \ e_i' \left[ \sum_{h=h}^{\infty} \sum_{l=0}^{h-1} C_l \hat{A} q_1 \hat{A}' C_l' \right] e_i,$$

s.t. $q_1 q_1' = 1,$ \hspace{1cm} (5)

where $q_1$ is a vector of unit length that represents a column of $Q$. Uhlig (2004b) shows that the maximization problem in (5) can be expressed as $Sq_1 = \lambda q_1$, where $S = \sum_{h=h}^{\infty} \sum_{l=0}^{h-1} (C_l \hat{A})' (e_i e_i') (C_l \hat{A})$.

To find the structural shock associated with the largest FEV of $y_{i,t}$ over $h = h \leq \bar{h}$, we need to find the eigenvector $q_1$ with the maximal eigenvalue $\lambda$ of the matrix $S$.

The Max Share approach by Francis et al. (2014) is a special case of the maximization problem (5), as it extracts the shock explaining the maximum FEV share of a variable in $Y_t$ at one horizon instead of cumulatively maximizing the FEV shares over all horizons from $h$ to $\bar{h}$.

### 3.2 An alternative identification of news shocks

To conduct our empirical analysis, we develop a novel identification of news shocks that combines the key ideas of the BS and KS methods. We need to deviate from the pure BS and KS methods because PTFP measures are not available for other countries, except for the U.S., and we use labor productivity instead. In contrast to PTFP, labor productivity is not adjusted for cyclical variations in factor utilization, which has implications for the identification of news shocks. For example, short-run shocks appear to more easily account for fluctuations in factor utilization over shorter horizons (Uhlig, 2004b). Consequently, to identify the news shocks using labor productivity, we need to isolate the two technology shocks from other structural shocks (e.g. demand shocks) that are likely to affect the cyclical component contained in labor productivity but are not allowed to affect the true productivity level of the economy.

Following the discussion in Section 2, technology is driven by two exogenous processes: (i) the unanticipated technology shocks that explain the largest share of fluctuations in the productivity level over shorter horizons and (ii) the anticipated (news) shocks that diffuse slowly over time and induce persistent changes in future productivity level.12 The key feature of the medium-run identification scheme in Uhlig (2004b,a) and Francis et al. (2014) is that while it extracts the shock series that is the dominant source of fluctuations in the productivity level at long horizons, it allows other shocks to play a role.13 Applying this medium-run identification scheme to a VAR with labor productivity is likely to extract a shock series containing both unanticipated and anticipated technology shocks. However, we need to disentangle the two technology processes as they have presumably different implications for the dynamics of the trade balance.

12 See, for example, Beaudry and Portier (2006), Barsky and Sims (2012), Kurmann and Otrok (2013), Barsky et al. (2015), Kurmann and Sims (2019).

13 In contrast, Galí (1999) assumes that unexpected technology shocks are the only source of fluctuations in the productivity level in the long run.
Intuitively, our news shocks identification approach consists of three steps. In the first step, given that predictable fluctuations in utilization become negligible at longer horizons (Barsky et al., 2015), we apply the FEV share maximization routine over the long horizon $h(1)$ to isolate the two technology shocks from other structural shocks. Thus, the resulting shock series contains both unanticipated and anticipated technology shocks.

In the second step, to separate the two technology processes, we exploit the idea that the short-run fluctuations in the technology measure are dominated by the unanticipated technology shocks. Thus, to isolate the short-run shocks, we use the same VAR specification as in the first step and extract the shock series with the largest contribution to fluctuations in the level of labor productivity over a short horizon $h(2)$. Importantly, in this setting, news shocks are allowed to affect labor productivity over the maximization horizon $h(2)$. Note that extracting the shock that maximizes the FEV share of labor productivity only on impact ($h(2) = 0$) is equivalent to the zero impact restriction of the BS model.

In the third step, the shock series containing both technology processes from the first step is regressed on the short-run shock series from the second step. The residuals from this regression represent the news shocks.

Our three-step identification scheme can be consolidated as follows. Following Cascaldi-Garcia and Galvão (2019), one can extract the news shocks by applying the QR-decomposition to the two eigenvectors that define the shocks in the first and second steps. Employing the QR-decomposition to both eigenvectors yields orthogonal vectors. While the first vector remains unchanged, the resulting second orthonormal vector is obtained by subtracting its projection over the first one, which is equivalent to the third regression step. Therefore, the eigenvector determining the short-run shock that we extract using the FEV share maximization horizon $h(2)$ must be ordered first. The new identification restrictions are thus obtained from the orthonormal “Q part” of the QR-decomposition. The second column of the “Q part” defines the main restrictions for the news shock, which we use to compute the impulse response functions (IRFs) in a standard VAR setting.

### 3.3 Specification of the FEV share maximization horizons

To make sure that our news shocks extracted from a SVAR with labor productivity as target variable satisfy the key features found in the literature (Beaudry and Portier, 2014), we carefully evaluate the specification of the FEV share maximization horizons $h(1)$ and $h(2)$ by comparing the results from the BER identification with the outcomes of the BS and KS models.

To determine the length of the FEV share maximization horizons $h(1)$ and $h(2)$, we consider the following three criteria:

1) The plausibility of the timing assumptions related to the short-run horizon $h(2)$ that we implement to separate the two technology processes using labor productivity as target variable. On the one hand, because labor productivity is not corrected for cyclical variations in factor utilization, it is likely to react immediately to a news shock and thus violate the zero impact
restriction $h(2) = 0$, which is the key identifying restriction in the BS model. On the other hand, truncating the short-run maximization horizon $h(2)$ at higher values is likely to capture not only the short-run shocks but also the news shock, since the contribution of the latter to fluctuations in the productivity level increases over time.

2) The plausibility of the IRFs of PTFP following our news shocks identified using labor productivity as target variable. Specifically, we need to ensure that our news shocks affect the future productivity level permanently and with the correct sign. Note that while a delayed and persistent rise in the aggregate level of productivity is the key identifying restriction of news shocks generally accepted in the literature, an immediate jump in the productivity level is the key feature of the unanticipated technology shock.

3) Our news shocks have to be highly correlated with the news shocks from the BS and KS models, which rely on PTFP as target variable.

Table 1: Forecast error variance decomposition

<table>
<thead>
<tr>
<th>Identification scheme</th>
<th>Target variable</th>
<th>Maximization horizon (quarters)</th>
<th>Percentage contribution of the news shocks to productivity variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>BS</td>
<td>PTFP-15</td>
<td>h = 0–40</td>
<td>(I) 0.0 4.1 16.7 15.8 14.7 15.3 2.1 1.4</td>
</tr>
<tr>
<td>KS</td>
<td>PTFP-15</td>
<td>h = 80</td>
<td>(II) 3.8 27.6 20.3 54.4 11.8 44.4 3.4 19.0</td>
</tr>
<tr>
<td>KS</td>
<td>LP</td>
<td>h = 80</td>
<td>(III) 11.2 35.9 22.4 63.5 8.8 55.2 2.7 36.1</td>
</tr>
<tr>
<td>BER</td>
<td>PTFP-15*</td>
<td>h(1) = 0–40</td>
<td>(IV) 19.0 41.9 27.4 69.4 8.3 61.1 2.8 45.3</td>
</tr>
<tr>
<td></td>
<td>LP*</td>
<td>h(2) = 0–2</td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** This table reports the percentage contribution of the news shocks obtained from different models to productivity variables at various forecast horizons. We obtain the news shocks from 7-variable VARs by applying the Barsky and Sims (BS), Kurmann and Sims (KS), and our alternative (BER) identification schemes. The target productivity variables in these models are, respectively, Fernald’s purified TFP published in 2015 (PTFP-15) and hourly labor productivity (LP). Besides the targeted productivity variables, the models in this table differ with respect to the specification of the horizons used in their medium-run identification schemes. The percentage contribution of the news shocks from these models to productivity variables denoted as PTFP-15* and LP* are obtained from 8-variable VARs that are estimated as a subset system of equations using the method of seemingly unrelated regressions where PTFP-15* and LP* enter the models as subset variables. The VARs are estimated with an intercept and four lags using quarterly data for the period 1960:1 to 2007:3. Details are discussed in the text.

To compare the results from the BER identification with the outcomes of the BS and KS models, we estimate the following 7-variable VARs using quarterly U.S. data. In each VAR, we use the 2015 vintage of PTFP (PTFP-15) and hourly labor productivity (LP), defined as the ratio of real GDP to total hours worked, as our measures of technology.14 Further, the VARs include real consumption of non-durables and services, real investment, total hours worked in the non-farm business sector, inflation measured as the growth rate of the GDP price deflator, the real stock price (nominal S&P 500 index deflated by the GDP price deflator), and consumer confidence (a qualitative index of five-year ahead business condition expectations).

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14Our VAR specification closely follows Barsky and Sims (2011) and Sims (2016). Because, in contrast to these studies, we use labor productivity instead of PTFP as our measure of technology to extract the news shocks, we deviate from their original specifications by not including real GDP in the VARs.
Consumption, investment, and hours are expressed in per capita terms by dividing the series by the civilian non-institutionalized population aged sixteen and over. All variables are specified in log levels, except for the inflation rate. The VARs are estimated with four lags and a constant over the period 1960:1–2007:3, excluding the period since the Great Recession.

We obtain the results for PTFP-15* and LP* from 8-variable VARs that are estimated as a subset system of equations using the method of seemingly unrelated regressions. That is, PTFP-15* and LP* are included one at a time and are ordered last in the extended 8-variable VARs (see, for example, Elstner and Rujin, 2019; Levchenko and Pandalai-Nayar, 2020).

Table 1 reports the FEV shares of PTFP-15 and LP explained by the news shocks. The results for models (I) – (III) are obtained following the original BS and KS identification schemes. In the BS model (I), we use PTFP-15 with the zero impact restriction and the FEV share maximization horizon of $h = 0 − 40$ quarters. In the KS model (II), we use PTFP-15 to extract the news shocks and set the FEV share maximization horizon to $h = 80$ quarters. The KS model (III) uses LP as target variable instead of PTFP-15. In the BER model (IV), our baseline identification scheme, we use LP and define the maximization horizon as $h(1) = 0 − 40$ in the first step and $h(2) = 0 − 2$ in the second step.

The selection of the FEV share maximization horizon $h(2) = 0 − 2$ in our baseline BER model (IV) is based on the following observations. First, the results in Table 1 show that news shocks explain a negligible FEV share of PTFP-15 in the short run, but become increasingly important at longer horizons. Note that the contributions of the news shock to fluctuations in PTFP-15 on impact in the BS models (I) is zero by assumption. By contrast, the contribution of the news shocks from the KS model (II) to fluctuations in both PTFP-15 and LP* is different from zero, though very low. Therefore, we rule out the orthogonality assumption between the news shock and labor productivity, that is $h(2) = 0$. Furthermore, the results in Table 1 indicate that the news shocks explain between 28 and 54 percent of fluctuations in LP (models (I)–(III)) at a horizon of four quarters and these results for PTFP-15 range between 4 and 20 percent. We are therefore cautious about truncating the short-run FEV maximization horizon $h(2)$ at a 4-quarter horizon, since it might capture news shocks together with other short-run shocks. Selecting a short-run FEV share maximization horizon of $h(2) = 0 − 2$ is in line with the near-zero contribution of the news shocks from the BS model (I) to PTFP-15 and results in plausible FEVD outcomes for our news shocks, as shown in the last two columns of Table 1.

Further, the BER identification with $h(2) = 0 − 2$ yields higher pairwise correlations between the structural news shocks from models (I)–(III) and our baseline news shocks obtained using higher horizon specification of $h(2)$. Comparing the correlations between the BS model (I) with the zero restriction, the KS model (II), and the BER model (IV) with zero impact restriction

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15 The macroeconomic aggregates are from the NIPA tables and all variables are available for download on the homepage of Eric Sims (see also Sims, 2016).

16 Following Barsky and Sims (2011), estimating the system in levels results in consistent estimates of impulse responses and is robust to cointegration of unknown form.

17 However, we find that our baseline results hold if we extract the news shocks using the alternative maximization horizon $h(2) = 0 − 4$ the second step of our BER identification while keeping $h(1) = 0 − 40$ unchanged.
Table 2: Correlations of U.S. news shocks

<table>
<thead>
<tr>
<th>Identification scheme</th>
<th>(I)</th>
<th>(II)</th>
<th>(III)</th>
<th>(IV)</th>
<th>(V)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Target variable</td>
<td>PTFP-15</td>
<td>PTFP-15</td>
<td>LP</td>
<td>PTFP-15</td>
<td>LP</td>
</tr>
<tr>
<td>Maximization horizon</td>
<td>h = 0–40</td>
<td>h = 80</td>
<td>h = 80</td>
<td>h(1) = 0–40</td>
<td>h(2) = 0</td>
</tr>
<tr>
<td></td>
<td>h(2) = 0–2</td>
<td></td>
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</tr>
</tbody>
</table>

Notes: This table reports the pairwise correlations of the U.S. news shocks. We obtain the news shocks from 7-variable VARs by applying the Barsky and Sims (BS), Kurmann and Sims (KS), and our alternative (BES) identification schemes. The target productivity variables in these models are, respectively, Fernald’s purified TFP published in 2015 (PTFP-15) and hourly labor productivity (LP). Besides the targeted productivity variables, the models in this table differ with respect to the specification of the horizons used in their medium-run identification schemes. The VARs are estimated with an intercept and four lags using quarterly data for the period 1960:1 to 2007:3. Details are discussed in the text.

yields highly correlated news shocks series (see Table 2). Our BER identification scheme in (V), however, relaxes the zero restriction and assumes instead that the short-run fluctuations in LP are dominated by unexpected technology and other short-run shocks over the horizon \(h(2) = 0 - 2\). This approach results in a news shock series that is highly correlated with the shock series from the BS model (I) 0.45 and with the shock series from the KS model (II) 0.74.

In addition, the correlations between the unanticipated technology shocks from the BS model (I) (not reported in Table 2) and the news shocks from the BER model (V) are close to zero, which indicates that our news shocks identification is successful in accounting for short-run fluctuations in the measure of technology driven by the unanticipated technology shocks.

To define the long-run FEV share maximization horizon \(h(1)\), we check the plausibility of the IRFs of PTFP following our news shocks identified using labor productivity as target variable. Figure 1 illustrates the IRFs of the variables in the VAR system to news shocks obtained from the BS model (I), KS model (II) with PTFP-15 and KS model (III) with LP. Our baseline BER model identifies the news shock using LP as target variable and the FEV share maximization horizons \(h(1) = 0 - 40\) and \(h(2) = 0 - 2\). Furthermore, we show the IRFs of the subset variables in the VARs—PTFP-15* and LP*. First, the response of PTFP-15* to our BER baseline news shocks is close to zero on impact and displays a gradual and persistent increase to a new long-run level in subsequent periods. By contrast, the BER model that specifies the FEV share maximization horizon \(h(1) = 80\), following the KS model, results in a negative short-run response of the PTFP-15* (not shown in Figure 1), which is an implausible response of technology to a news shock and was discarded.

The results in Figure 1 corroborate the key features of a positive news shock that is associated with a persistent increase in consumption. After an initial decline, the response of hours worked to a news shock follows a hump-shaped pattern before returning to its pre-shock level.

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Figure 1: Impulse responses following a U.S. news shock

Notes: This figure shows the IRFs to U.S. news shocks obtained from 7-variable VARs by applying the following identification schemes: Barsky and Sims (BS) model (I) with purified TFP published in 2015 (PTFP-15) as target variable; Kurmann and Sims (KS) model (II) with purified TFP published in 2015 (PTFP-15) and KS model (III) with hourly labor productivity (LP) as target variables; and our BER baseline model with hourly labor productivity (LP) as target variable. Besides the targeted productivity variables, the models in this figure differ with respect to their identification approach. The IRFs for the variables denoted as PTFP-15* and LP* are obtained from 8-variable VARs that are estimated as a subset system of equations using the method of seemingly unrelated regressions where PTFP-15* and LP* respectively, enter the models as subset variables. The VARs are estimated with an intercept and four lags using quarterly data for the period 1960:1 to 2007:3. Details are discussed in the text. The shaded areas are the 68% and 95% confidence intervals corresponding to the BER baseline model, which are based on the recursive-design wild bootstrap procedure by Gonçalves and Kilian (2004).

The impact decrease in hours is consistent with a wealth effect of news shocks emphasized in the literature (see, for example, Barsky and Sims, 2011; Kurmann and Sims, 2019). In contrast,
inflation declines immediately following a news shock.\footnote{The impact response of inflation for the BS model (I) in Figure 1 is similar to the evidence in \textcite{Sims2016}.} Stock prices increase strongly on impact and display a mild but persistent hump-shaped response in the following periods after the shock.

Thus, our BER identification using LP as target variable and the FEV share maximization horizons $h(1) = 0 - 40$ and $h(2) = 0 - 2$ is successful in accounting for the short-run movements in the non-technological component contained in labor productivity and in isolating news shocks from other shocks that are likely to affect productivity in the short run. Furthermore, our news shock affect the future productivity level in a gradual and persistent manner.

In sum, our news shocks identification offers a flexible setting for isolating unanticipated and anticipated (news) technology shocks. An important advantage of our identification over the BS approach is that we relax the controversial restriction of impact orthogonality between news and the measure of technology.

4 Empirical model and results

4.1 Baseline model

\textit{Data and VAR specification}

Our baseline VARs for the G7 countries include seven country-specific variables and two variables capturing global developments.\footnote{Data sources and definitions are summarized in the Data Appendix A.1.} We use internationally harmonized, quarterly labor productivity measures (ratio between real GDP and hours worked) as our target variables to extract the news shocks. To compute these measures, we use quarterly series of total hours worked contained in the dataset of \textcite{OhanianRaffo2012}.\footnote{The dataset is available on Andrea Raffo’s website. Hours worked are constructed to be internationally consistent and may, therefore, slightly deviate from the official series. For example, the correlation between the constructed and the official growth rates of total hours worked for the U.S. is 0.89.}

The key variable of interest in our analysis is the trade balance, defined as the ratio of nominal net exports (exports minus imports of goods and services) to nominal GDP. The terms of trade are defined as the relative price of imports to exports, that is a decline in this variable signals an improvement/appreciation of the terms of trade (\textcite{BackusKehoeKydland1994,EndersMueller2009}). Further, the VARs include private consumption, investment, hours worked, and the GDP deflator. We convert the first three variables in per capita terms using population in the age between 15 to 64 years, which avoids introducing additional trends. Private consumption, investment, and the GDP deflator inflation serve as forward-looking variables in our analysis.

To control for external productivity developments, we include a measure of labor productivity for the rest of the world (ROW), which is computed for each country in our sample. To do so, we first aggregate the growth rates of labor productivity for the remaining G7 countries
(excluding the country under consideration, each at a time) by weighting each country’s series by its share in total hours worked. We then use the aggregate growth rates to construct an index of a ROW productivity measure for each country separately. Several studies use relative productivity measures to identify idiosyncratic unexpected productivity or news shocks (Enders and Müller, 2009; Corsetti et al., 2014). This approach, however, assumes that a substantial fraction of the news shocks determined with this relative measure originates from the respective domestic country, which seems to hold for the U.S. but presumably not for the other smaller economies.

Finally, it is crucial to control for external commodity prices as the terms of trade represent an important transmission channel for international wealth effects. We, therefore, include a measure of the real oil price, which is defined as the WTI spot price divided by U.S. CPI.

All variables are specified in log-levels, except for the real oil price, GDP deflator, and the terms of trade, which are specified in log-differences. For the latter variables we show the cumulative IRFs. The country-level VARs are estimated with four lags and an intercept. The time period covered by our data is 1974:1 to 2016:4. The starting point of our analysis in 1974 is chosen to coincide with the start of the floating exchange rate period after the collapse of the Bretton Woods system (Fratzscher and Straub, 2013).

Identification

We compute the dynamic effects of idiosyncratic (country-specific) news shocks by applying the baseline BER and the KS identification approaches to each country-level VAR, as outlined in Section 3. In addition, we assume that idiosyncratic news shocks determined using both identification approaches are not allowed to affect the ROW labor productivity and the real oil price on impact. These assumptions imply that our identified news shocks are purged from contemporaneous exogenous global developments. These zero impact restrictions seem to be problematic for the U.S. However, the key results for the U.S. hold if we estimate a 7-variable VAR that excludes the ROW labor productivity and the real oil price. The results are shown in Appendix C. The 95%-confidence intervals are based on the recursive-design wild bootstrap procedure by Gonçalves and Kilian (2004).

We also show the responses of variables that are not included in the baseline 9-variable VARs. Specifically, we study the effects of news shocks on real exports, real imports (both defined in per capita terms), the nominal and real exchange rate, and the short-term interest rate. To this end, we estimate 10-variable VARs as a subset system of equations using the method of seemingly unrelated regressions. That is, these variables enter the country-level VARs as subset variables one at a time and are ordered last in the extended 10-variabe VARs. Thus, we identify the news shocks as in the baseline 9-variable VARs and are able to compute the IRFs for the additional variable under consideration. To compute the results for the G7 countries, we use the mean group panel estimator, which is simply the average of the IRFs across the G7 countries.
Following Hoffmann (2003), trade balance positions are mainly driven by idiosyncratic shocks (see also Marquez, 2002; Bussière, Fratzscher, and Müller, 2010). To examine whether we identify idiosyncratic news shocks, we check their correlations across countries. Low pairwise correlations suggest that the news shocks indeed capture a country-specific component and vice versa (Hoffmann, 2003). The pairwise correlations are close to zero in all cases. Thus, there is no evidence that our news shocks are affected by global factors in any sizable way.

4.2 Results

Figure 2 illustrates that on average across the G7 countries (henceforth referred to as the G7 countries), we do not find that a favorable news shock has a negative effect on the trade balance. By contrast, for the U.S. economy, we find a significant deterioration of the trade balance, which is in line with a large literature (see, for example, Fratzscher and Straub, 2013; Nam and Wang, 2015). These findings are similar for both the BER and the KS approaches. The difference in the trade balance adjustments is largely driven by the reaction of imports and to a lesser extent by the responses of exports.

Our baseline approach shows for the U.S. a short-lived drop in exports and a larger in magnitude increase in imports. These responses combined exert a negative effect on the trade balance. By contrast, the terms of trade appreciate significantly, which compensates the drop in exports and thus acts as a trade balance stabilizer. Therefore, the reaction of imports to a positive news shock is the dominant source of fluctuations in the U.S. trade balance. For the G7 countries, we find that the trade-related variables react significantly different compared to the U.S. Though exports and imports rise by roughly the same magnitude, the slight appreciation of the terms of trade amplifies the positive reaction of exports and thus leads to a slight improvement of the trade balance.

The fall in U.S. exports can be explained by the significant appreciation of the real exchange rate (see Figure D.1 in Appendix D), which is also reflected in the movements of the terms of trade. Nam and Wang (2018) explain this appreciation by a strong increase in domestic absorption while the effect of technological news shock on output has not yet materialized, which induces higher domestic inflation. However, we cannot confirm this explanation as Figure D.1 shows that the GDP deflator declines following a news shock.

The real appreciation could be caused by the Balassa-Samuelson effect. The latter implies an increase in non-traded goods prices following a favorable news shock, which raises the domestic price level. However, the terms of trade appreciate by roughly the same amount as the real exchange rate and thus point to rising export prices. This finding suggests that the real appreciation of the U.S. currency is not driven by the Balassa-Samuelson effect.

In our view, the appreciation of the U.S. terms of trade and the real exchange rate is rather caused by nominal exchange rate movements, which reflect market expectations. We assume

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22 These results are available upon request.
23 This finding is in line with Corsetti et al. (2014), who identify U.S. technology shocks for the manufacturing sector by employing sign restrictions and find no significant response of the U.S. real exports.
that a positive news shock lowers domestic inflation expectations compared to the rest of the world for a protracted period of time, which ultimately causes the nominal and real appreciation of the U.S. currency. In contrast to the U.S., the nominal exchange rate in the G7 countries does not react to a news shock, see Figure D.1 in Appendix D. This observation masks, however, quite different reactions across the single countries.

Concerning U.S. imports, we stress the role of domestic absorption, which is mainly the result of private consumption and investment decisions. Figure 3 shows that both consumption and investment display a positive hump-shaped response. For the G7 countries, we also find that both consumption and investment increase after a news shock. However, while the magnitude of the consumption response is quite similar for the U.S. and the G7 countries, the rise in investment is much stronger for the U.S. economy.

The rise in consumption may have different sources. An anticipated improvement in future growth prospects is associated with a positive wealth effect that causes a decline in households’ savings. As a result, households with access to financial markets increase their consumption expenditures. Fratzscher and Straub (2013) emphasize that the strength of the wealth effect depends on the financial market depth and the equity home bias of countries. They find a strong wealth effect for the U.S., which has a deep equity market and a large share of equity wealth is held domestically. Furthermore, a reduction in the real interest rate can also stimulate current consumption expenditures. This explanation points to an important role of monetary policy for the reaction of domestic demand after a news shock.

An increase in investment can be due to several factors: First, the increase in consumption expenditures spurred by positive technology news induces higher sales’ expectations of firms. As a result, firms invest more to increase their productive capacity. Second, firms expect a higher marginal capital productivity for a given capital stock and real interest rate, which induces more investment. Third, monetary policy could lower its nominal interest rate, which spurs investment activity. Kurmann and Otrok (2013) show empirically for the U.S. economy that positive news causes a decline in the short-term interest rate. Our baseline results provide similar evidence in Figure D.1. Fourth, under certain conditions, news shocks causes an increase in hours worked. Jaimovich and Rebelo (2008, 2009) and Kamber et al. (2017) discuss this in a theoretical framework. The increase in hours worked might cause investment to increase as more workers require a capital stock. The sign and magnitude of investment, however, depend on a multitude of model parameters, see our discussion in Section 2.

We explain the stronger reaction of U.S. investment compared to other G7 countries with the following observations. First, in our baseline results show that U.S. hours worked decline after a positive news shock, which rules out this explanation for the stronger U.S. investment response. Second, higher sales’ expectations of U.S. firms due to higher consumption spending also does not seem to be the driving force of the large U.S. investment reaction. Third, we find that monetary policy responds to a fall in inflation by lowering its interest rate. The cut in nominal interest rates is larger than the decline in inflation resulting in a decline in the real interest rate, which stimulates U.S. investment activity. However, this monetary policy channel
Figure 2: Impulse responses of trade-related variables to a news shock

Notes: This figure shows the IRFs of trade-related variables to country-specific news shocks for the group of the G7 economies, the U.S., Japan, and France. The IRFs and confidence intervals for the G7 economies are the respective means obtained using the country-specific IRFs and confidence intervals. The country-level VARs include: labor productivity for the rest of the world, real oil price, country-specific labor productivity, real consumption per capita, real investment per capita, total hours worked per capita, GDP deflator, the trade balance, and the terms of trade. All variables are specified in log-levels, except for the real oil price, GDP deflator, and the terms of trade, which are specified in first log-differences. For the terms of trade we report the cumulative IRFs. The terms of trade are defined as the relative price of imports to exports—a fall implying an appreciation. The country-level VARs are estimated with four lags and an intercept using quarterly data for the period 1974:1 to 2016:4. We obtain the IRFs to news shocks by applying, respectively, the baseline BER and the Kurmann and Sims (KS) identification approaches to 9-variable VARs country-by-country. In addition to the news shocks identification approaches introduced in Section 3, we identify the idiosyncratic news shocks by also including two zero impact restrictions on, respectively, labor productivity for the rest of the world and the real oil price. The IRFs for exports and imports (defined in real per capita terms) are obtained from 10-variable VARs that are estimated as a subset system of equations using the method of seemingly unrelated regressions where exports and imports, one at a time, enter the country-level VARs as subset variables. Shaded areas are 68% and 95% confidence intervals corresponding to our baseline IRFs based on the recursive-design wild bootstrap procedure (Gonçalves and Kilian, 2004).

cannot be observed across other G7 countries. Thus, we infer that the monetary policy transmission channel has an important role in generating a more dynamic reaction of U.S. investment compared to other G7 countries. Finally, other factors that distinguish the U.S. economy from
other G7 countries might play a role in explaining the strong investment response. For example, Elstner and Rujin (2019) highlight the attractiveness of the U.S. domestic market for investment activity compared to other advanced economies due to its loose service and labor market regulations.

Figure 3: Impulse responses of macroeconomic variables to a news shock

Notes: This figure shows the IRFs of macroeconomic variables to country-specific news shocks for the group of the G7 economies, the U.S., Japan, and France. For details see notes to Figure 2. Shaded areas are 68% and 95% confidence intervals corresponding to our baseline IRFs based on the recursive-design wild bootstrap procedure (Gonçalves and Kilian, 2004).

Focusing on other countries, we find for Japan particularly interesting results. Similar to the U.S., domestic absorption in Japan increases strongly after a news shock, and the rise in investment is even larger compared to the U.S. However, the Japanese trade balance responds positively to a news shock. One explanation lies in the strong appreciation of the terms of trade, which by far exceeds the respective appreciation in the U.S. variable. Furthermore, Japanese exports increase in response to a news shock, whereas the U.S. exports decline. One possible source behind the divergent dynamics of exports between the two countries could be the nature of their respective technological gains. Corsetti, Martin, and Pesenti (2007) document
that technological gains that reduce the cost of producing existing goods (process innovations) deteriorate the terms of trade. By contrast, technological gains that reduce the cost of creating new firms and product varieties (product innovations) can improve the terms of trade. Consequently, new high-price product varieties increase the domestic export prices relative to its import prices. Thus, one explanation could be that the firms in the Japanese export sector focus more on product innovations compared to U.S. export-oriented firms. Nonetheless, we stress that the improvement in the Japanese terms of trade is mainly driven by the large nominal appreciation of the Yen (see Figure D.1).

Figure 4: Impulse responses to news shocks for selected G7 countries

Notes: This figure shows the IRFs of macroeconomic aggregates to country-specific news shocks for Germany, the U.K., Italy, and Canada. For details see notes to Figure 2. Shaded areas are 68% and 95% confidence intervals corresponding to our baseline IRFs based on the recursive-design wild bootstrap procedure (Gonçalves and Kilian, 2004).

The results for France provide another example where a positive news shock causes a rise in the trade balance. In contrast to the U.S., we find that consumption and investment decline after a favorable news shock. This might reflect a weak wealth effect. A further explanation could be that in France compared to the U.S., a larger share of households are financially
constrained, that is they have no perfect access to financial markets. The decline in investment is to some extent caused by the fact that monetary policy does not react aggressively enough to counteract the substantial decline in inflation, which leads to a rise in the real interest rate. Further, a pronounced decline in hours worked after a news shock lowers capital stock requirements and thus investment.

The transmission channels of news shocks highlighted for the U.S., Japan, and France can be also used to discuss the results of the remaining G7 countries: Germany, the U.K., Italy, and Canada. Figure 4 summarizes the results for these countries for the key variables: The trade balance, the terms of trade, consumption, and investment. It is apparent that the results are highly heterogeneous across countries. For example, for Germany, similar to the U.S., we find that a positive news shock has a negative effect on the trade balance. The deterioration of the trade balance is mainly driven by the increase in domestic absorption, which points to the standard transmission channels (like the wealth effect). In contrast to Japan and the U.S., our baseline results show for the German terms of trade display only a short-lived and slight appreciation. For Italy and Canada, we observe an increase in the trade balance. For both countries we would suggest similar transmission channels of news shocks as discussed for France. For the U.K., we find similar to Japan, that the strong appreciation of the terms of trade in the first quarters outweighs the strong increase in domestic absorption and thus triggers an increase in the trade balance.

5 Robustness checks

To corroborate our baseline results, we have analyzed a number of robustness exercises and extensions. As previously reported, we checked the sensitivity of our main findings with respect to the restriction that the idiosyncratic news shocks are orthogonal to innovations in the real oil price and in ROW labor productivity. To do so, we re-estimated the VARs excluding the latter two variables. The results summarized in Appendix C show that our baseline statements remain unaffected by these zero impact restrictions. We further evaluated the specification of the FEV share maximization horizon \( h(2) \) that captures the short-run shocks. Specifically, we set \( h(2) = 0 - 4 \) and obtained similar results.\(^{24}\)

In this section, we provide three further checks: First, we replace hourly labor productivity with a utilization-adjusted TFP measure determined using the approach proposed by Imbs (1999). Second, we evaluate the impact of an alternative restriction concerning global unanticipated technology and news shocks. Finally, we estimate our baseline VARs using Bayesian methods subject to a Minnesota prior to address the large number of coefficients.

The first check addresses the target technology measure. Ideally, we would use a utilization-adjusted technology measure like PTFP provided by Fernald (2014) for the U.S. Since such series are not available for other countries, we instead rely on labor productivity as target technology

\(^{24}\)These results are available upon request.
measure in our baseline calculations. In this robustness check, we construct utilization-adjusted TFP measures for the G7 countries following the approach of Imbs (1999) and Levchenko and Pandalai-Nayar (2020). To compute these measures, we need to calibrate several model parameters. In our applications, we closely follow Imbs (1999) and Levchenko and Pandalai-Nayar (2020) by using the same parameter values. Details of this procedure are explained in Appendix B.

Figure 5: Robustness checks (I)

Notes: This figure shows the IRFs of macroeconomic aggregates to country-specific news shocks for the group of the G7 economies, the U.S., Japan, and France. For details on the baseline model see notes to Figure 2. Shaded areas are 68% and 95% confidence intervals corresponding to our baseline IRFs based on the recursive-design wild bootstrap procedure (Gonçalves and Kilian, 2004). The BVAR posterior median IRFs are obtained from the estimations of our baseline VARs via Bayesian methods subject to a Minnesota prior. The global technology IRFs are obtained from the estimations of our baseline VARs in which the maximization horizon to extract the global technology shock is defined as \( h = 0 - 80 \). The IRFs for the utilization-adjusted TFP are obtained from the estimations of our baseline VARs with utilization-adjusted TFP instead of hourly labor productivity as target technology measure.

\footnote{We thank Andrei A. Levchenko and Nitya Pandalai-Nayar for sharing their Matlab code with us.}

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Figure 6: Robustness checks (II)

Notes: This figure shows the IRFs of macroeconomic aggregates to country-specific news shocks for Germany, the U.K., Italy, and Canada. For details on the baseline model see notes to Figure 2. Shaded areas are 68% and 95% confidence intervals corresponding to our baseline IRFs based on the recursive-design wild bootstrap procedure (Gonçalves and Kilian, 2004). The BVAR posterior median IRFs are obtained from the estimations of our baseline VARs via Bayesian methods subject to a Minnesota prior. The global technology IRFs are obtained from the estimations of our baseline VARs in which the maximization horizon to extract the global technology shock is defined as $h = 0 - 80$. The IRFs for the utilization-adjusted TFP are obtained from the estimations of our baseline VARs with utilization-adjusted TFP instead of hourly labor productivity as target technology measure.

We re-estimate our baseline VARs replacing labor productivity with the new utilization-adjusted TFP series for the G7 countries. The green lines with diamond markers in Figures 5 and 6 summarize the results for the key variables of interest in our analysis: The trade balance, the terms of trade, private consumption and investment. The blue lines with circle markers and confidence intervals refer to our baseline results. For the average of the G7 countries and the U.S., we find that the IRFs are very close to each other for the two specifications, confirming our main conclusions. While the trade balance in the U.S. deteriorates after a favorable news shock, this is not the case for the G7 countries.
However, the results for Italy and Japan reveal notable differences. We attribute these differences to certain parameter assumptions that are required to compute the utilization-adjusted TFP measures. One example is the calibration of the steady state interest rate \((r)\). Imbs (1999) and Levchenko and Pandalai-Nayar (2020) assume \(r\) equal to 4 percent per year, which seems implausibly high for Japan in recent decades. Given the sensitivity of this utilization-adjusted TFP measure with respect to model parameter assumptions, we are cautious about using it as our target technology measure in the baseline VARs.

In the second analysis, we test the sensitivity of our baseline results with respect to the identification assumption concerning global productivity developments. To do so, we modify the identification restrictions applied to ROW labor productivity. In our baseline VARs, we separate idiosyncratic shocks from the unanticipated movements in the ROW labor productivity by assuming that the latter is not affected contemporaneously by idiosyncratic news shocks.

In the following, we extend this approach by controlling for global unanticipated technology and news shocks in our idiosyncratic news shock series. Using our baseline VARs, we identify a global technology shock by maximizing the FEV share of ROW labor productivity over the horizon between 0 and 80 quarters. Note that we cumulatively maximize the FEV shares over all horizons from impact onward. Following the expositions in Section 3, this makes us confident that we indeed control for both unanticipated technology and news shocks. To obtain idiosyncratic news shocks, we apply the identification approach outlined in Section 3. In addition, our idiosyncratic news shocks are orthogonalized with respect to the new global technology shock series by applying the QR-decomposition. The black lines with square markers in Figures 5 and 6 show the results. Except for the U.K., our main statements are barely affected by this modification.

The final robustness check relates to the large number of estimated coefficients in our baseline VARs. We need to include many variables in our VARs as we want to reproduce the large information set of the economic agents who form their expectations regarding future technological developments. One drawback of this approach, however, is that the high number of included variables affects the estimation precision with possible harmful consequences for the impulse response analysis. To address this issue we estimate Bayesian VARs using the Minnesota prior (Litterman, 1986). Specifically, we assume for the Minnesota prior that all variables follow a random walk process. The identification of the news shocks is the same as in Section 4.

The magenta lines with cross markers in the Figures 5 and 6 illustrate the posterior median IRFs of the Bayesian VARs. In almost all cases, the posterior median IRFs are similar to our baseline results.

6 Conclusions

This study provides new evidence on the effects of news shocks on the trade balance for the G7 countries. Since the utilization-adjusted technology measures are not available for the G7 countries, except for the U.S., we rely on labor productivity as our target technology measure.
To isolate anticipated technology shocks, we develop a novel news shocks identification. We think that our identification approach might also be of interest for other empirical applications, which so far have relied on the Barsky and Sims (2011) identification approach to detect anticipated shocks while being critical about the embedded zero restriction. Examples are the identification of anticipated government spending shocks (Ben Zeev and Pappa, 2017) and the detection of investment-specific news shocks (Ben Zeev and Khan, 2015).

Regarding our research question, we find that while in the U.S. and Germany, news shocks induce a deterioration of the trade balance, in other G7 countries, news shocks have positive trade balance effects. In our view, the differences in the trade balance effects across the G7 countries are mainly due to heterogeneous reactions of labor markets, wealth effects, and monetary policy. We stress the important role of the terms of trade and nominal exchange rate movements in explaining trade balance dynamics following a news shock. Even a strong increase in domestic absorption after a favorable news shock does not necessarily lead to a deterioration of the trade balance.

Overall, we conclude that productivity-enhancing changes in technology that improve domestic growth prospects do not necessarily lead to a fall in the trade balance or, in a broader view, the current account balance. This result is particularly relevant in light of economic policy recommendations raised by international organizations that emphasize the negative link between the fluctuations in the trade balance and growth prospects. For example, the EU Commission repeatedly claims in its in-depth reviews on the prevention and correction of macroeconomic imbalances that further reform progress to unleash Germany’s growth potential will help to strengthen investment and contribute to a lower trade surplus in the country over time.26 The German Council of Economic Experts does share the Commission’s view that measures should be taken to increase the potential output growth. However, the Council is more careful regarding the impact on the German trade balance. It emphasized this judgment “irrespective of whether the measures are capable of reducing the current account surplus”. It does rightly so in view of our empirical results for Germany.27

References


26See, for example, European Commission (2016, 2019) and International Monetary Fund (2019).

27See German Council of Economic Experts (2014), p. 35. See also Gros and Busse (2013).


Appendices

A Data definitions and sources

Table A.1: Data sources and definitions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definitions and sources</th>
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</thead>
<tbody>
<tr>
<td><strong>Fernald (2014), <a href="http://www.johnfernald.net/TFP">http://www.johnfernald.net/TFP</a></strong></td>
<td>The 2015 vintage of utilization-adjusted quarterly-TFP series by John Fernald and Andrew Tai. The data on inputs, including capital, are used to produce a quarterly series on total factor productivity. In addition, the dataset implements an adjustment for variations in factor utilization—labor effort and the workweek of capital. The utilization adjustment follows Basu, Fernald, and Kimball (2006). Further details on the derivation of this measure can be found in Fernald (2014).</td>
</tr>
<tr>
<td><strong>Utilization-adjusted quarterly-TFP series for the U.S. Business Sector</strong></td>
<td><strong>Ohanian and Raffo (2012) dataset, <a href="http://andrearaffo.com/araffo/Research.html">http://andrearaffo.com/araffo/Research.html</a></strong> Total hours worked series for the G7 countries are obtained as the product of hours worked per worker and employment. Further details on the derivation of this measure can be found in Ohanian and Raffo (2012). We use internationally harmonized, quarterly labor productivity measures for the G7 countries, defined as the ratio between real GDP and total hours worked. To compute these measures, we use quarterly series of total hours worked contained in the dataset of Ohanian and Raffo (2012). The real GDP series are from the OECD Economic Outlook (EO) database and available in the dataset of Ohanian and Raffo (2012).</td>
</tr>
<tr>
<td><strong>Hourly labor productivity</strong></td>
<td><strong>Sims (2016) dataset, <a href="https://www3.nd.edu/~esims1/tpf_vintage.html">https://www3.nd.edu/~esims1/tpf_vintage.html</a></strong> U.S. time series for the previous draft by Sims (2016) and the current paper by Kurmann and Sims (2019). We use the following variables: hourly labor productivity (LP), defined as the ratio of real GDP to total hours worked, real consumption of non-durables and services, real investment, total hours worked in the non-farm business sector, inflation measured as the growth rate of the GDP price deflator, the real stock price (nominal S&amp;P 500 index deflated by the GDP price deflator), and consumer confidence (a qualitative index of five-year ahead business condition expectations). Consumption, investment, and hours are expressed in per capita terms by dividing the series by the civilian non-institutionalized population aged sixteen and over. The macroeconomic aggregates are from the NIPA tables and all variables are available for download on the homepage of Eric Sims.</td>
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Table A.1: (Continued from previous page)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definitions and sources</th>
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<tbody>
<tr>
<td>Other variables</td>
<td></td>
</tr>
<tr>
<td>Real private consumption per capita</td>
<td>The real private consumption expenditures for the G7 countries are from the OECD QNA database and are defined as follows: National currency, volume estimates, OECD reference year, annual levels, seasonally adjusted. We convert the real private consumption in per capita terms using population aged 15 to 64. Population series are from national statistical offices and the OECD EO database.</td>
</tr>
<tr>
<td>Real private gross capital formation per capita</td>
<td>The real private gross capital formation series for the G7 countries are from the OECD QNA database and are defined as follows: National currency, volume estimates, OECD reference year, annual levels, seasonally adjusted. We convert the real private gross capital formation series in per capita terms using population aged 15 to 64. Population series are from national statistical offices and the OECD EO database.</td>
</tr>
<tr>
<td>GDP deflator</td>
<td>The GDP deflator for the G7 countries is computed as the ratio of nominal to real GDP. The nominal GDP series are from the OECD QNA database and are defined as follows: National currency, current prices, annual levels, seasonally adjusted. The real GDP series are from the OECD QNA database and are defined as follows: Expenditure approach, National currency, volume estimates, OECD reference year, annual levels, seasonally adjusted.</td>
</tr>
<tr>
<td>Trade balance</td>
<td>The trade balance series for the G7 countries are computed as the ratio of nominal net exports (exports minus imports of goods and services) to nominal GDP. The exports of goods and services series are from the OECD QNA database and are defined as follows: External balance of goods and services—exports of goods and services, national currency, current prices, annual levels, seasonally adjusted. The imports of goods and services series are from the OECD QNA database and are defined as follows: External balance of goods and services—imports of goods and services, national currency, current prices, annual levels, seasonally adjusted. The nominal GDP series are from the OECD QNA database and are defined as follows: National currency, current prices, annual levels, seasonally adjusted.</td>
</tr>
<tr>
<td>Terms of trade</td>
<td>The terms of trade for the G7 countries are defined as the relative price of imports to exports. The import deflator series are from the OECD QNA database and are defined as follows: External balance of goods and services—deflator of the imports of goods and services, national currency. The export deflator series are from the OECD QNA database and are defined as follows: External balance of goods and services—deflator of the exports of goods and services, national currency.</td>
</tr>
<tr>
<td>Real oil price</td>
<td>The real oil price is defined as the WTI spot price divided by U.S. CPI. The Spot Crude Oil Price is from the Federal Reserve Economic Data (FRED) database and is defined as follows: West Texas Intermediate (WTI), dollars per barrel, quarterly, not seasonally adjusted. The consumer price pndex for all urban consumers is from the FRED database and is defined as follows: All Items in U.S. city average, index 1982-1984=100, quarterly, seasonally adjusted.</td>
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Notes: Table continued on the next page.
Table A.1: *(Continued from previous page)*

<table>
<thead>
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<tbody>
<tr>
<td><strong>Subset variables</strong></td>
<td></td>
</tr>
<tr>
<td>Real exports per capita</td>
<td>The real exports series for the G7 countries are from the OECD QNA database and are defined as follows: National currency, volume estimates, OECD reference year, annual levels, seasonally adjusted. We convert the real exports in per capita terms using population aged 15 to 64. Population series are from national statistical offices and the OECD EO database.</td>
</tr>
<tr>
<td>Real imports per capita</td>
<td>The real imports series for the G7 countries are from the OECD QNA database and are defined as follows: National currency, volume estimates, OECD reference year, annual levels, seasonally adjusted. We convert the real imports in per capita terms using population aged 15 to 64. Population series are from national statistical offices and the OECD EO database.</td>
</tr>
<tr>
<td>Nominal effective exchange rate</td>
<td>The nominal effective exchange rate series for the G7 countries are from the Bank of International Settlements (BIS) and are defined as: Narrow indices 2010 = 100.</td>
</tr>
<tr>
<td>Real effective exchange rate</td>
<td>The real effective exchange rate series for the G7 countries are from the BIS and are defined as: Narrow indices 2010 = 100.</td>
</tr>
<tr>
<td>Short-term interest rate</td>
<td>The short-term interest rate series for the G7 countries are from the OECD Main Economic Indicators database.</td>
</tr>
<tr>
<td>Shadow rate</td>
<td>The shadow rate series are determined by Krippner (2013, 2014). The International Shadow Short Rates estimates for the U.S., euro area, Japan, and the U.K. are available for download on the website of the Reserve Bank of New Zealand</td>
</tr>
</tbody>
</table>

*Notes: All definitions are from the original sources. The data set covers G7 countries: Canada (CA), France (FR), Germany (DE), Italy (IT), Japan (JP), the U.K., and the U.S.*
The utilization-adjusted TFP series for the G7 countries

To construct the utilization-adjusted TFP series for the G7 countries, we use the procedure introduced by Imbs (1999) and recently adopted by Levchenko and Pandalai-Nayar (2020). Imbs (1999) relies on a growth accounting framework to compute TFP (Solow residual). Furthermore, he corrects the Solow residual for capital utilization and labor effort. Based on the insight that cost-minimizing firms operate on both observed and unobserved utilization margins simultaneously, Imbs (1999) shows that unobservable input utilization can be related to observable variables. Thus, the key issue in the computation of the utilization-adjusted TFP is the estimation of the series on capital utilization and labor effort, which are derived as functions of observable variables and certain parameter values.

Consider the following aggregate production function with constant returns to scale:

\[ Y_t = X_t(K_tU_t)^{(1-\alpha)}(N_tE_t)^{\alpha}, \]

where \( Y_t \) is output, \( K_t \) denotes the capital stock, and \( N_t \) defines total hours worked. Effective labor input is defined as a product of labor effort \( E_t \) and total hours worked. The effective capital services are defined as the product of the capital utilization rate \( U_t \) and the capital stock. The variable \( X_t \) defines the utilization-adjusted TFP.

The algorithm to compute the utilization-adjusted TFP comprises the following steps:

1. We use the perpetual inventory method to construct the starting capital stock series from the official investment series \( I_t \) and a quarterly average depreciation rate set to \( \delta = 0.025 \). The initial value of the capital stock is obtained from \( K_0 = I_1/(r + g_I) \), where \( g_I \) is the average growth rate of investment and \( r \) is the average interest rate. We tested our results with respect to other choices for the initial capital stock with no significant changes in the final outcomes of the utilization-adjusted TFP measure.

2. The starting capital utilization series \( U_t \) is computed using the capital stock series \( K_t \) from the previous step, \( Y_t \), \( \delta \), and \( r \) from the equilibrium relationship \( U_t = (Y_t/K_t)^{\delta/r} \), where \( Y/K \) is the average period value.

3. Construct the time-varying depreciation series \( \delta_t \) from \( \delta_t = \delta U_t^{1+r/\delta} \). \( U_t \) defines the starting capital utilization series from step (2).

4. Use the time-varying depreciation rate \( \delta_t \) from the previous step and the official investment series to construct the capital stock series using the standard capital accumulation equation \( K_{t+1} = (1 - \delta_t)K_t + I_t \). To do so, use \( K_0 \) determined in step (1) as initial value of the capital stock.

For a detailed discussion and derivation see Imbs (1999) and Levchenko and Pandalai-Nayar (2020).
5. Use the new average depreciation rate $\bar{\delta}$ based on the time-varying depreciation series $\delta_t$ from step (3) and the capital stock series $K_t$ from step (4) to compute a new capital utilization series $U_t$ as described in step (2).

6. Iterate until the capital stock series $K_t$ and $\bar{\delta}$ converge. Then construct the final capital utilization series $U_t$.

7. The household’s labor effort $E_t$ is derived using data on consumption $C_t$, real wages $W_t$, and total hours worked $N_t$ from the expression $E_t = \left( \frac{\alpha Y_t}{C_t} \right)^{1/(1+\psi)}$, where $\psi = \frac{\alpha W_t N_t}{Y_t} - 1$. Given $\alpha$ and the observed average ratio $W_t N_t / Y_t$, we can compute the parameter $\psi$ required to obtain the labor effort series $E_t$.

8. Compute the utilization-adjusted TFP from the production function presented in equation B.1.

The data on nominal wages is obtained from the OECD National Account database. Other data series are described in Appendix A.
C Results for 7-variable VAR models

Figure C.1: Impulse responses of trade-related variables to a news shock

Notes: This figure shows the IRFs of trade-related variables to country-specific news shocks for the group of the G7 economies, the U.S., Japan, and France. The IRFs and the confidence intervals for the group of the G7 economies are the respective means obtained using the country-specific IRFs and the confidence intervals. The country-level baseline VARs include: labor productivity for the rest of the world, real oil price, country-specific labor productivity, real consumption per capita, real investment per capita, total hours worked per capita, GDP deflator, the trade balance, and the terms of trade. The 7-variable VARs include similar variables as in the former case, except for the labor productivity for the rest of the world and the real oil price. All variables are specified in log-levels, except for the real oil price, GDP deflator, and the terms of trade, which are specified in first log-differences. For the terms of trade we report the cumulative IRFs. The terms of trade are defined as the relative price of imports to exports—a fall implying an appreciation. The country-level VARs are estimated with four lags and an intercept using quarterly data for the period 1974:1 to 2016:4. We obtain the IRFs to news shocks by applying, respectively, the baseline BER and the Kurmann and Sims (KS) identification approaches to VARs country-by-country. The IRFs for exports and imports (defined in real per capita terms) are obtained from, respectively, 10-variable and 8-variable VARs that are estimated as a subset system of equations using the method of seemingly unrelated regressions where exports and imports, one at a time, enter the country-level VARs as subset variables. Shaded areas are 68% and 95% confidence intervals corresponding to our baseline IRFs based on the recursive-design wild bootstrap procedure (Gonçalves and Kilian, 2004).
Figure C.2: **Impulse responses of macroeconomic variables to a news shock**

Notes: This figure shows the IRFs of macroeconomic variables to country-specific news shocks for the group of the G7 economies, the U.S., Japan, and France. For details see notes to Figure C.1. Shaded areas are 68% and 95% confidence intervals corresponding to our baseline IRFs based on the recursive-design wild bootstrap procedure (Gonçalves and Kilian, 2004).
Figure C.3: Impulse responses to a news shock for selected G7 countries

Notes: This figure shows the IRFs of macroeconomic aggregates to country-specific news shocks for Germany, the U.K., Italy, and Canada. For details see notes to Figure C.1. Shaded areas are 68% and 95% confidence intervals based on the recursive-design wild bootstrap procedure (Gonçalves and Kilian, 2004).
D IRFs of prices, exchange rates, and monetary policy

Figure D.1: Impulse responses to news shocks

Notes: This figure shows the IRFs of the GDP deflator, the terms of trade, the real and nominal effective exchange rates, and of the short-term interest rate to country-specific news shocks for the group of the G7 economies, the U.S., Japan, and France. For the U.S. and France, the interest rate is replaced by the shadow rate determined by Krippner (2013, 2014) starting from 2008:1. For Japan we use the shadow starting from 1995:1. Results do not change using the official interest rate for the entire sample period. The IRFs and the confidence intervals for the group of the G7 economies are the respective means obtained using the country-specific IRFs and the confidence intervals. The country-level baseline VARs include: labor productivity for the rest of the world, real oil price, country-specific labor productivity, real consumption per capita, real investment per capita, total hours worked per capita, GDP deflator, the trade balance, and the terms of trade. All variables are specified in log-levels, except for the real oil price, GDP deflator, and the terms of trade, which are specified in first log-differences. For the GDP deflator and the terms of trade we report the cumulative IRFs. The terms of trade are defined as the relative price of imports to exports—a fall implying an appreciation. An increase in the real and nominal effective exchange rates implies an appreciation. The country-level VARs are estimated with four lags and an intercept using quarterly data for the period 1974:1 to 2016:4. We obtain the IRFs to news shocks by applying, respectively, the baseline BER and the Kurmann and Sims (KS) identification approaches to VARs country-by-country. In addition to the news shocks identification approaches introduced in Section 3, we identify the idiosyncratic news shocks in the 9-variable VARs by also including two zero impact restrictions on, respectively, labor productivity for the rest of the world and the real oil price. The IRFs for the real and nominal effective exchange rates and the short-term interest rate are obtained from 10-variable VARs that are estimated as a subset system of equations using the method of seemingly unrelated regressions where these three series, one at a time, enter the country-level VARs as subset variables. Shaded areas are 68% and 95% confidence intervals corresponding to our baseline IRFs based on the recursive-design wild bootstrap procedure (Gonçalves and Kilian, 2004).
Notes: This figure shows the IRFs of the GDP deflator, the terms of trade, the real and nominal effective exchange rates, and of the short-term interest rate to country-specific news shocks for Germany, the U.K., Italy, and Canada. For Germany, the U.K., and Italy, the interest rate is replaced by the shadow rate determined by Krippner (2013, 2014) starting from 2008:1. Results do not change using the official interest rate for the entire sample period. For details see notes to Figure D.1. We obtain the IRFs to news shocks by applying, respectively, the baseline BER and the Kurmann and Sims (KS) identification approaches to VARs country-by-country. The IRFs for the real and nominal effective exchange rates and for the short-term interest rate are obtained from 10-variable VARs that are estimated as a subset system of equations using the method of seemingly unrelated regressions where these three series, one at a time, enter the country-level VARs as subset variables. Shaded areas are 68% and 95% confidence intervals corresponding to our baseline IRFs based on the recursive-design wild bootstrap procedure (Gonçalves and Kilian, 2004).